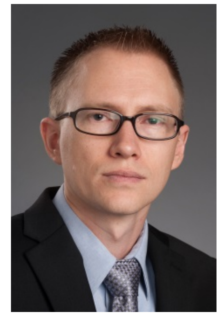
Will a New Input Strategy Be Warranted in Non-Irrigated Corn Production under Global Climate Change? An Analysis Using Corn Production in the Midwestern United States



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Abstract

Incentives to delay agricultural inputs to increase output and protect against climate change and weather related risk are explored. When producer decision making in non-irrigated production in an environment of weather uncertainty is outlined an incentive is found when imperfect information and risk is present. The EPIC crop simulator is then used to assess the yield impact of fertilizer delaying in the non-irrigated corn component of corn-soybean rotations in Humboldt and Webster Counties, Iowa. Assessed in conjunction with disaster frequency data, crop simulations suggest optimal input timing to be six weeks or more after planting. Additional production considerations such as spring field conditions and fertilizer runoff also support a six week or later input delay strategy. This result held under both recent weather conditions and climate change projections through 2040. The strength of each component's influence on the input delaying decision changes however. Disaster frequency, field conditions, and runoff considerations all increase the incentive to delay fertilizer inputs while the risk associated with yield loss from delaying fertilizer beyond the six week mark also increases while the increase in yield benefits decreases relative to recent conditions. Methods to incentivize adoption of delayed input practices are briefly outlined such as modification of the farm bill's multi-peril crop insurance program while being reserved for greater discussion in later research on the soy side of corn-soybean rotations.

Introduction

This research analyzes decision making and methods of risk mitigation in agricultural environments containing uncertainty. The environment of analysis is non-irrigated corn production in two major corn producing counties in Iowa where risks come in many forms, weather being foremost. Adding further to volatility, the region is undergoing unprecedented climate change, which changes the risks associated with productivity in ways impossible to fully predict. This investigation follows a specific progression: 1) Provide a framework for decision making in agricultural environments of uncertainty, attuned to the practices of agricultural production. 2) Establish a climate change risk mitigation strategy based on the developed framework. 3) Consider management practices in the agricultural environment that may be used to implement strategies. 4) Test implications of alternative choices using crop simulation tools. 5) Suggest strategies within existing policy framework to incentivize alternative management practices. Implementation of this analytical framework using a realistic production scenario produces results applicable in the specific case chosen while presenting a framework for risk mitigation strategy development in non-irrigated production environments undergoing climate change in general.

First, this paper frames the research question in the decision making environment being analyzed. The incentives faced by non-irrigated corn producers are considered. Disaster declaration frequency in Iowa is used to roughly approximate the warranted delay in production input timing to minimize risk in a repetitive production environment. A crop simulation model is then used to assess the effects on yield and profit of potential risk reducing input delay strategies. Simulations are conducted under both recent weather conditions and projections of

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a downscaled climate model through 2040. Additional effects on the production environment and producer behavior are then considered using data on field conditions, agricultural input prices, and environmental impacts. Finally, adjustments to crop insurance policies are briefly considered to incentivize adoption of risk reduction strategies in the U.S. production environment. Such strategies will be explored in greater detail in later work. The findings from this endeavor suggest a mix of incentives and disincentives exist for delayed input strategies. The crop simulator and decision making matrix used identify incentives from increased average yield as well as reduced disaster susceptibility. The variability in yield, however, is projected to increase under future growing conditions when a delayed input strategy is used. Thus, willingness of producers to attempt such changes in farm management will be highly dependent on tastes and preferences. Specific, temporary agricultural policies could help overcome such change and risk aversion, allowing producers to explore these results in their farm specific context.

Background

Climate change mitigation or adaption is also especially important in developing economies where agricultural production is a critical component. However, United States non-irrigated corn production was chosen due to greater availability of data. Corn production in Iowa, America's top corn producing state, was chosen. Iowa corn producers contribute 17% to national production (USDA NASS, 2013) and have a remarkable impact not just on local economies, but also nationally across industries. Corn is perhaps the most pervasive production input in the U.S. due to its use in many forms in numerous foods, livestock feed, nonfood products, and use as a fuel additive. Due to this pervasiveness of a single commodity, at least some part of every dollar spent in the U.S. economy goes toward the price of corn production. Beyond price, the alarming reliance on a single commodity, which is increasing globally, compels research into safeguarding and optimization of production.

Our top corn producing state is undergoing unprecedented changes (Iowa Climate Change Impacts Committee, 2012) in temperature, precipitation, and frequency of extreme weather events, continuing a trend of change begun several decades ago. The changing climate will impact agricultural producers, altering their production choices and potentially changing management practices. Non-irrigated corn producers have generally applied fertilizer at planting due to concerns of irreparable yield loss from nitrogen deficiency if applied later. However, climate change related risk compels review of this input decision. Some agronomical field research suggests potential yield gains from delaying fertilizer under certain conditions, the benefit of such a delay may increase as the climate changes. A number of other potential benefits to delaying application are stated in the agricultural literature: avoiding wet spring field conditions, labor demand smoothing, reduced water pollution from fertilizer runoff, and increased availability of information about weather and likelihood of a successful growing season.

Literature Review

To begin, a discussion of the literature on effects of extreme weather events and climate change on non-irrigated production as well as input timing on corn must be discussed. A good place to begin is the journal article that inspired this research, Magnan, Lybbert, Mrabet, and Fadlaoui's *The quasi-option value of delayed input use under catastrophic drought risk: The case of no-till in Morocco* (2011). In this article, a new farming practice (no-till) was compared to traditional farming practices under the circumstances of increased drought occurrence in Morocco. The motivating factor is climate change induced increases in drought probability, from one in eight years, to one in two years in the research area. This led to a discussion of whether it would be in the best interests of farmers to adopt practices allowing them to delay inputs until later in the season. Presumably, at a later date more will be known about the likelihood of drought for instance, a point in time after the first and critical early season rains should have occurred. Their analysis of a change in practice to no-till agriculture began under current, already adverse conditions, and then proceeded into a climate change scenario with further increases in drought probability. The result was that delaying inputs through no-till caused a small loss under current conditions because of the author's assumption in the model of no-till being less productive than traditional tillage due to lack of farmer experience. Under increasing drought probability, a small benefit is indicated in the scenario outlined. The author's method is based on only one possible in season input option, leaving room for improvement through the use of a crop simulation model to assess the effects of all potential input points on yield.

Cherkauer and Mishra (2010) explore two relevant hypotheses, first that their area of interest became wetter during the last several decades, and second, that drought during different plant growth periods of corn and soybeans has different impacts on yield. It was found, agreeing with prior research such as Shaw (1988), drought during silking and grain fill is more devastating for corn production, followed by moisture stress in the 30 days prior to silking. Earlier droughts, if mild, have little impact on yields and thus season success. Their research correlates impacts of a limited number of different factors on corn production, something that can be expanded on through use of a crop simulation model such as the Environmental Policy Integrated Climate (EPIC) model. Unfortunately, based on this research producers would have to delay inputs until late in the production cycle to avoid application in years where the crop is lost from extended droughts. This would entail significant yield reductions in non-drought years according to section five of my research.

What is the expected climate change in the central Iowa research area? One issue with applying climate change predictions on a small geographic scale is the abundance of competing climate models, emission predictions, and methods of downscaling of data. However, a report from the Environmental Protection Agency regarding climate change specific to Iowa and a statement by 138 leading scientific research faculty and staff representing 27 Iowa colleges and universities gives a rough overview (EPA, 2011; Iowa Climate Statement, 2012). According to these sources, Iowa's climate has become increasingly warm over the last three decades and is expected to continue to warm 2.5-7.2 degrees Fahrenheit on average in the future. Further, Iowa is expected to become wetter in addition to warmer, asymmetrically throughout the year and more extreme weather events, i.e. complete soil saturation and flashing flooding, stifling heat waves, and devastating droughts are likely to occur. Nearly all additional rainfall is expected early in the growing season while less rain is expected mid-season. Weather extremes are the kind of events my research is intended to account for in decision making and find policies to mitigate, whether inhibitive soil saturation and flooding or lack of rainfall to support production.

Scharf, Wiebold, and Lory (2002) discuss possible benefits and yield losses of delaying nitrogen in non-irrigated corn production, providing a significant overview of the literature relating to nitrogen timing. They found little to no loss, and sometimes even an increase in yields from delaying nitrogen in non-irrigated corn production. They also mention a number of additional benefits to input delaying such as labor demand smoothing by shifting it to slower periods in the season, reduced fertilizer runoff, and more precise fertilizer need assessment. The authors, however, do not attempt to quantify the additional benefits to delaying of nitrogen application. Using the vegetative state scale where V1 represents emergence of the first leaf on corn stalks and V20 signifies when all leaves have emerged and silking has begun, it was found in numerous agronomy field experiments that nitrogen can be delayed well into the season with no loss or even a small gain until the V11 stage and only a little yield loss (<3%) until V16. The loss from V16-V20 is significant, however, suggesting a decision point at V11 or V16 for fertilizer application if a risk reducing delayed application strategy is used. Scharf, Wiebold, and Lory's findings sharply contrast with the reportedly commonly held belief among farmers that irreversible yield loss will occur if nitrogen application is delayed.

The literature on pesticide/herbicide/fungicide application, however, finds application of defensive expenditures cannot be delayed until much later in the season. Carey & Kells (1995) and Tharp & Kells (1999) provide evidence such defensive expenditures cannot be delayed beyond growth stage V4, approximately 4-5 weeks into the Iowa growing season, or corn crops face catastrophic loss from resource competition and damage, as it was found that weed growth can be modelled exponentially. And so in section four of this research, herbicide, fungicide, and pesticide defensive applications will be considered part of the initial input package in period one.

A number of sources discuss the effects of adjusting one, a pair of inputs, or drought/moisture stress in agronomy experiments. However, as changes in each input impact crop response to other inputs, research on impacts of climate change, coupled with changes in inputs, must utilize crop simulation models that account for multiple changes in factors. To put the issue in perspective, moisture stress impacts yield to different extents during different periods of corn production. Drought during silking and grain fill are most significant, but moisture stress within the 30 days prior also has significant, though different yield reducing impacts. According to Shaw (1988), a recognized expert on corn production and agronomy in Iowa, moisture stress days in the pre-silking period result in an approximately 2.9% reduction in yield per day of moisture stress. In contrast, volume of rainfall, in addition to endangering crops at extremes, effects rates of plant growth directly as well as the rate of fertilizer loss through runoff. The interaction of all other inputs and changes in production parameters must be considered. The most important input after water availability is nitrogen fertilizer. When rainfall is ideal, fertilizer is the strongest indicator of yield. But during significant drought years, fertilizer cannot preserve yield and total crop loss can still occur. During mild drought years, the role of fertilizer is less consistent. Further, when fertilizer and rainfall are ideal, the limiting issue then is temperature. Both low and high temperatures are detrimental to production and effect yield to different degrees depending on other factors. Each of these factors and many others interact, effecting yields in different ways depending on the set and timing of production factors present each season.

Decision-Making in Agriculture with Production Uncertainty

This discussion of climate change mitigation strategies relies on an analysis of likely outcomes from delaying agricultural inputs. First, producer decision making for risk reduction in a climate of uncertainty is discussed while the local disaster record is used to ascertain a first approximation of optimal risk reducing input timing. Then, an agricultural production simulation is conducted to assess the effect on yield. And finally, an exploration of additional impacts on production and the environment are explored.

Decision making obviously varies substantially with context. In a neoclassical profit maximizing, perfect information environment producers would know at the beginning of a year whether the crop will be successful and how to produce maximum yields with the inputs available. It isn't the case, however, that agricultural producers hold perfect information or anything even close or are even necessarily profit maximizers. In this discussion of producer decision making, both neoclassical assumptions are modified. Profit maximization in agriculture should entail choosing the crops and production methods that maximize profit. In this model it is instead assumed agricultural producers choose to produce a specific crop. In the EPIC simulation that follows corn is chosen as part of corn-soybean biennial rotations, regardless of other crop options available. This is a minor point for most of the analysis, simply reducing the variables by one, the crop. In contrast, modification of the perfect information assumption has major implications. Infusion of risk into production places a burden on producers to consider input choices that may trade yield in individual years for risk reduction across a lifetime of production. A decision making matrix is developed in section four within this context of imperfect information and yield maximization constrained by the presence of risk.

The price of corn reflects the costs of production, risk, and global supply and demand. Global supply and demand are outside the confines of this paper. The simplified model presented holds corn producers as corn producers, regardless of such influences. Costs of production, heavily influenced by a number of external factors such as input demands across agriculture, is also effected by risk at the farm level when viewed from a multiyear perspective. In an individual year, the cost of production is determined by the cost of inputs. Yet in multiyear production, the cost is the price of initial inputs, any reapplications necessary due to weather and pest induced losses, and the cost in yield of those losses. Consider a scenario where, shortly after seed planting and application of fertilizers, herbicides, pesticides, and applicable labor, strong downpours lead to flooding and a total loss of all inputs. If the afflicted farmer replants the crop that year, the cost of production would be two times the seed, fertilizer, herbicide, pesticide, and applicable labor necessary to produce one season's crop. While some inputs cannot rationally be delayed, yield is heavily dependent on optimal planting timing (Farnham, 2001), and herbicide deferral allows exponential growth in resource competing weeds (Carey & Kells, 1995; Tharp & Kells, 1999). Other inputs such as fertilizer show promise as loss reducers through delayed application. In this section, the rationale for delaying agricultural inputs is presented through a discussion of decision making in agricultural environments containing uncertainty.

Decision making on input timing when faced with risk

Naturally a farmer makes a profit, breaks even, or experiences a loss from production in a season. The breakeven point is where gross income meets cost, but this says nothing about how the costs and decisions are distributed within a season. Regardless of how the farmer distributes cost, the producer's goal within the given parameters is to maximize profit, which is the remainder after price multiplied by yield per acre (*PQ*) has subtracted a cost function (*C*), which includes land (*L*), seed (*S*), fertilizers (*F*), defensive expenditures on pesticides, herbicides, fungicides (*D*), harvest & postseason costs (generally referred to here as harvest, *H*), and labor divided into associated tasks such that L_L, L_S, L_F, L_D, and L_H respectively. To ensure comparability between farms, the total profit function of a farmer, where N represents the number of acres, can be considered on a per acre basis in a homogenous field environment. For simplicity, labor costs include the costs of equipment used in conjunction with that labor. The total profit function for a farmer using traditional tillage (*T*) is

$$\pi_T = N\{PQ - C[L(L, L_L) + S(S, L_S) + F(F, L_F) + D(D, L_D) + H(H, L_H)]\} \tag{1.1}$$

and per acre, it simplifies to

$$\pi = PQ - C[L(L, L_L) + S(S, L_S) + F(F, L_F) + D(D, L_D) + H(H, L_H)] \tag{1.2}$$

The farmer's profit possibilities are well known

Profit if $PQ > C$ (1.3)

Break even if $PQ = C$ (1.4)

Loss if $PQ < C$ (1.5)

Farmers do not know what P or Q will be at the start of a season but are assumed to know what input costs are as they can purchase inputs at this point. In reality, farmers can secure price through contracts, though it may not necessarily be advantageous to do so. This model considers rainfed, non-irrigated production and while P is determined by the market which considers both irrigated and non-irrigated corn production, Q is heavily dependent on weather encountered by the individual farmer. Dryland producers are at a disadvantage to irrigated farmers who have greater control over expected yield and can aim for optimal moisture provision, though they too will be affected by flooding, extended droughts, and other extreme weather events. And so, over a number of years, non-irrigated producers will have lower average yields and less profit within an area than irrigated neighbors. If P takes into account production and losses of yield across the market, it will under-compensate for losses to non-irrigated producers and over-compensate irrigated producers in any year with extreme weather events. While irrigating farmers can expect more consistent yields through partial control of moisture, dryland producers have little predictability in what year a drought or flood will occur. But in both cases, as the growing season progresses, knowledge on weather, yield probability, and market price at harvest improve. A number of other underlying assumptions in this model are made explicit in appendix A.

There are four major input decision scenarios possible, two under traditional tillage ($\overline{T}$) and two under no-till ($\overline{NT}$) production. Under each tillage decision, there are two scenarios, one where the farmer makes the decision on all inputs and applies them at the earliest point, planting, and one where the farmer applies minimal inputs at planting and has a second input decision at a later stage in the production process similar to Magnan, Lybbert, Mrabet, and Fadlaoui's (2011) treatment. A less interesting decision also exists at harvest (I_H). Because till versus no-till is not a significant cost issue in the U.S., unlike Morocco and much of the developing world where it is a major consideration, no-till is included in appendix B while the body of this paper focuses on traditional tillage agriculture. In the U.S., significant mechanization (part of L in the model) makes the till versus no-till cost difference minor compared to developing economies where less mechanization occurs and so this paper instead considers changes in fertilizer timing and related expenditures due to their significant usage and cost in the U.S. The no-till case, however, leads to some interesting conclusions as well on its effectiveness in climate change mitigation in the developing versus developed world. As such, readers with an interest in developing economies are especially encouraged to compare this section's decision making matrix to appendix B.

Under $\overline{T}$ any farmer conducting non-irrigated production decides to plant each acre if P_e and Q_e multiply to exceed costs of production

$$P_eQ_e > C(L, S, F, D, H) \tag{2.1}$$

However, the timing a farmer introduces inputs L, S, F, D, H is significant. For a traditional farmer, the expected profit function at planting is

$$\pi_e = P_eQ_e - I_1(L, S, F, D) - I_H(H) \tag{2.2}$$

In equation 2.2, the farmer provides all production inputs at seeding, and the only other input decision is harvest when the farmer can decide if the crop produced is worth harvesting. Under normal and mild water stress conditions the answer to the I_H decision is affirmative. The only time a farmer would decide not to harvest at I_H is if

$$P_eQ_e < I_H \tag{2.3}$$

Interpreted, this would be a circumstance of catastrophic, complete loss (Q_e or $P_e \approx 0$) and no mitigating income can be gained from what is available on the field. So under all but complete crop failure, the traditional decision making farmer faces the entire input decision at planting when the least information is known such that

$$\pi_e = P_eQ_e - C(L, S, F, D, H) \tag{2.4}$$

By equation 2.4, the farmer has no control over profitability after planting and is reliant on an increasingly unpredictable climate. In comparison, a farmer who divides inputs into two decision points, plus the decision to harvest, has greater control over loss mitigation and thus profitability when struck with adverse conditions. Such a producer has the profit function

$$\pi_e = P_e Q_e - I_1(L, S, D) - I_2(F) - I_H(H) \tag{2.5}$$

Again, except under total loss the harvest decision is positive and the function becomes

$$\pi_e = P_e Q_e - I_1(L, S, D) - I_2(F, H) \tag{2.6}$$

At I_2 more is known about the condition of the crop and season and a more accurate decision can be made on the value of continuing the season's production. A farmer producing per equation (2.5) or (2.6) can enjoy delaying significant costs until later in the season. At decision point I_2 the farmer's decision is

profit expected, continue production	$P_e Q_e - I_1 > I_2$	(2.7)
break even, indifferent	$P_e Q_e - I_1 = I_2$	(2.8)
additional inputs result in greater loss, go on vacation	$P_e Q_e - I_1 < I_2$	(2.9)

In a year where P, Q, and C are favorable, the traditional farmer and the input delaying farmer face the same costs and profits. But in comparing equations (2.4) and (2.6) in light of equations (2.7) through (2.9), the losses in meteorologically poor production years differ significantly with different input strategies.

In an adverse weather year, traditional farmers lose	$-\pi = C(L, S, F, D, H) - PQ$	(2.10)
or in a total loss year lose	$-\pi = C(L, S, F, D)$	(2.11)
In an adverse weather year, two-decision farmers lose	$-\pi = C(L, S, F, D, H) - PQ$	(2.12)
or in a total loss year lose	$-\pi = C(L, S, D)$	(2.13)

Taking the decision to produce further requires data on prices, operating costs, and more troublesome risk in an area. An assessment of the Iowa disaster record is used for a first approximation of whether an adjustment to input timing is warranted when risk is included in the agricultural decision process. A six week fertilizer input delay after planting is suggested for optimal yields per the next section of this research. This would entail fertilizer application around June 6th if the optimal planting date for the area of April 25th is used. This would allow reductions in losses in years with catastrophic events occurring from the last week of April through the first week of June, a time period corresponding with the highest disaster declaration frequency as in figure 1. Given the current price of fertilizer (Duffy, 2013), each acre where fertilizer is not applied and the crop subsequently lost, leads to a savings of $105-$135. For a producer experiencing the same extreme weather events but applying fertilizer at planting, the additional loss will be borne by the producer, crop insurer and ultimately by consumers. While delays until the yield optimizing six week mark remove some risk, it may be worthwhile to consider further delays in input commitment based on specific price and markets in each production year.

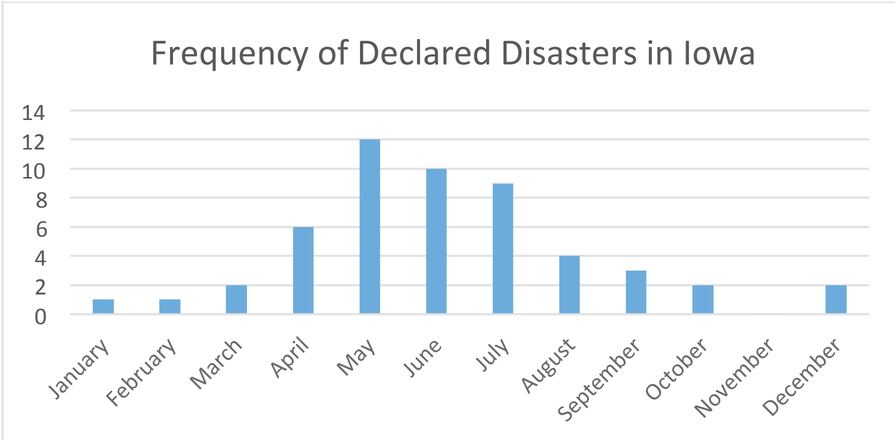

Figure 1. Monthly frequency of presidentially declared disasters in the state of Iowa for the period 1951-2013.

Limitations

The most significant limitation is scale of data on loss events. Drought is comparatively consistent in an area compared to flooding, tornados, and hail. Comparisons of county yields to declared disasters show a number of mismatched years. The effects of flooding in 1993 and 2010 are clear in Humboldt County and Webster County yields while the effects of other events are not. Next, many losses are not handled by disaster declaration. A thorough analysis of both crop insurance payouts and disaster data would certainly add to such a discussion. This would, however, be misdirected at the county or larger scale. Many events effect producers differently across a county, for instance flooding will be highly dependent on field location. But in general, disaster declaration data suggests risk is greater during the May-July portion of Iowa's production season.

EPIC Agronomical Simulation

To explore changes in optimum yield timing with changes in climate, the EPIC model is used to build on the preceding decision making matrix. EPIC is a process based crop simulator meeting the need for a model that simultaneously considers multiple parameters and their interactions as changes occur. It also has an extensive history of successful implementation in the agricultural literature. Here EPIC is calibrated to represent farms and production practices in Humboldt County and Webster County, Iowa. While historical daily weather data is used during a validation period, 1990-2010, spatially and temporally downscaled weather projections from the CSIRO Mk3 Climate System Model are used to represent the period 2011-2040. To explore the effects of input timing on yield, repeated simulations are conducted with fertilizer applied at different points within production seasons. The effect of input timing on yield is compared under the recent historical weather record to the projected climate of 2011-2040. Beginning four weeks prior to planting, fertilizer application is simulated at two week intervals through the twentieth week after planting. The subsequent fertilizer dependent yield curves demonstrate how yield is affected by fertilizer application on average. Comparison of the fertilizer input timing curves for the period 1990-2010 to 2011-2040 demonstrates how climate change affects yield maximizing incentives in the crop selected for analysis.

The objective of this component is to identify optimal input timing and the tradeoff with delaying input decisions in non-irrigated corn production under present conditions, and then to assess how optimality and the tradeoff will differ with climate change. Here the impact of climate change and input delaying in the specific cases of Humboldt and Webster counties Iowa, are explored as well as a process to assess such impacts on other environments. For adequacy of data, these two locations are chosen in the U.S. and specific agricultural operations simulated. Representative farms for Humboldt and Webster Counties, Iowa, approximately at latitudes/longitudes (42.58, -94.20) and (42.42, -94.19) respectively, are used for simulations of corn-soybean crop rotations. Corn-soybean rotations are the most common corn production method in the U.S. due to the beneficial byproducts of soy production on corn yields in the following year. A remarkable byproduct of soybean production is nitrogen development in the soil, a byproduct of many legume crops caused by bacteria in their root systems that convert atmospheric nitrogen into a form useable by crops. Nitrogen availability is one of the major determinants of corn yield and quality. Fertilizers are the second largest cost in U.S. corn production after land, and soy-corn-soy rotations have repeatedly been determined to be the most profitable long run production strategy.

The Environment Productivity Integrated Climate (EPIC) model is a process based, farm level agricultural production simulator (Williams, Jones, & Dyke, 1984; Sharpley & Williams, 1990), which has been used in numerous agricultural and environmental impact studies. EPIC operates on a daily time step, using multiple inputs and production parameters to determine crop output plus a number of related statistics. Crop growth, soil quality, farm management practices, production inputs, and weather properties are all considered. Brown and Rosenberg (1997) provide an adequate overview of each input's importance, interplay in EPIC, and effects on yield in a general case whose simulation area includes Iowa. General crop parameters, management practices, and locational properties have been refined in EPIC through years of application, validation, and program feedback from cases across the U.S. and abroad. The simulation is then calibrated for the specific case being considered. Daily weather data for the historical period comes from the National Oceanic and Atmospheric Administration (NOAA), National Weather Service (NWS), and Cooperative Observer Program (COOP), included in EPIC for the period 1960-2010. For Humboldt and Webster counties, the Fort Dodge 5 NNW weather station (station ID: GHCND: USC00132999) provides the weather data for both counties. Simulated monthly weather (temperatures and precipitation) for the period 2011-2040 comes from a 1/8 degree downscaled CSIRO Mk3 Climate System Model (Bureau of Reclamation, 2013; Gordon et al., 2002) of the Intergovernmental Panel on Climate Change (IPCC) A1B scenario (IPCC, 2007) run through the MODAWEC daily weather generator (Liu, Williams, Wang, & Yang, 2009) to produce the appropriate daily weather input for EPIC. Soil compositions for both counties are selected using the USDA National Resource Conservation Service (NRCS) Web Soil Survey (WSS) (USDA NRCS, 2012). Simulations are created to represent the vast majority, approximately 80%, of the soil composition of the representative farm areas chosen, with production yields weighted by proportion of each soil.

Table 1. Soil properties of representative farms

Location	Soil (Code)	Percent of Total Farm Area
Humboldt County	Canisteo clay loam, 0-2% slope (507)	40.5%
(42.58˚N, 94.20˚W)	Clarion loam, 2-5% slope (138B)	19.7%
	Nicollet loam, 1-3% slope (55)	12.7%
	Webster silty clay loam, 0-2% slope (107)	12.3%
	Total percentage of soil represented:	85.2%
Webster County	Canisteo clay loam, 0-2% slope (507)	25.2%
(42.42˚N, 94.19˚W)	Clarion loam, 2-5% slope (138B)	13.0%
	Nicollet loam, 1-3% slope (55)	20.5%
	Webster silty clay loam, 0-2% slope (107)	20.3%
	Total percentage of soil represented:	79.0%

Due to the unfeasibility of delaying herbicides, pesticides, and fungicides in practice, damage from weed competition, pests, and mildew as well as the effectiveness of defensive expenditures was simplified out of the model, only showing up implicitly in the calibrated crop harvest index.

There are multiple climate change scenarios available and the quantity and variety of projections grows with each IPCC assessment. For this analysis one scenario is chosen, the IPCC fourth assessment A1B scenario. In addition to effecting the specific CSIRO Mk3 climate model projection selected, the A1B scenario determines the CO2 level. NOAA annual CO2 levels from Muana Loa Observatory (NOAA ESRL GMD, 2012) are used for the historical period while the IPCC fourth assessment A1B CO2 projections are used for 2011-2040. The assessment report presents decadal stepped increases in CO2, which are extrapolated on an annual basis assuming steady annual increases in CO2 between projections. I considered using historical monthly variations in CO2 to simulate monthly variations for the projected simulation period. Effectively, it would cause a small CO2 reduction in the growing season and increasing CO2 in the off season, leading to slightly reduced yields across all years. This, however, is saved for other research. A limitation to note about EPIC is its inability to account for disasters such as flooding. So during a year where flooding hits an area, yields are only affected to the extent that excess rainfall affects yields, not to the extent of crops and topsoil being swept away. The projections of the chosen climate scenario versus current weather are presented in figures 2 through 5.

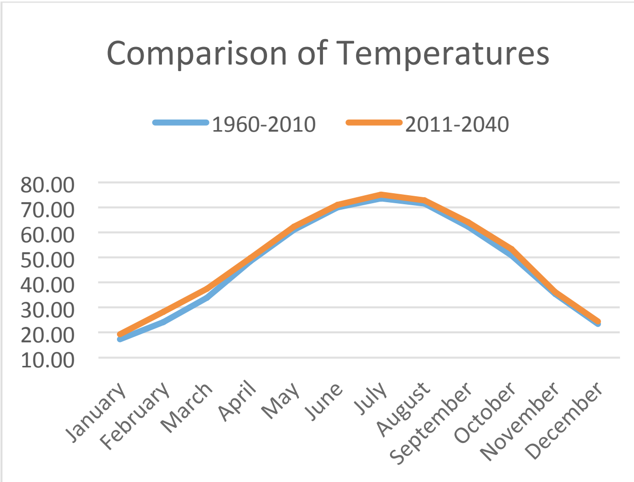

Figure 2. Comparison of average temperature for period 1960-2010 versus 2011-2040.

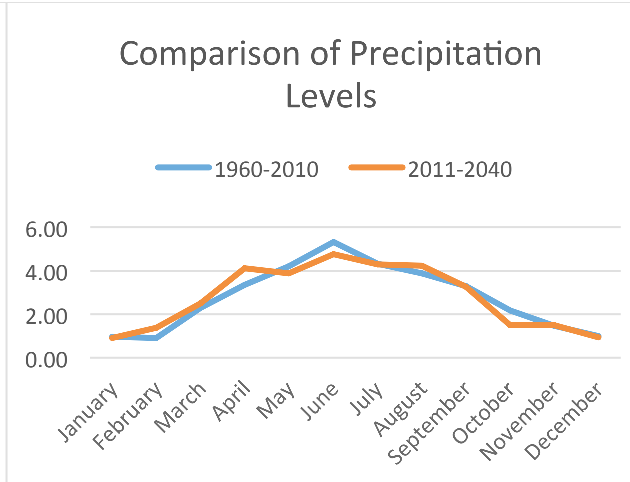

Figure 3. Comparison of average precipitation levels for period 1960-2010 versus 2011-2040.

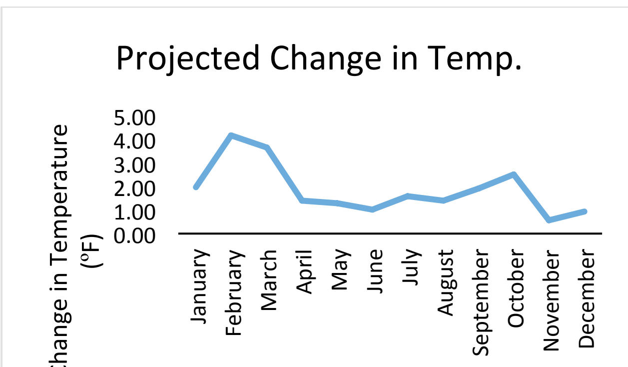

Figure 4. Change in temperatures for the period 2011-2040 versus baseline period 1960-2010.

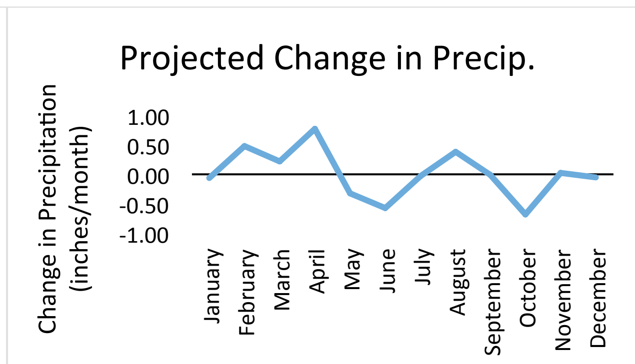

Figure 5. Change in monthly precipitation levels for the period 2011-2040 versus baseline 1960-2010 period.

Daily climate generation information

There is a temporal mismatch between projections from established climate models and needs of process based agricultural simulations. While CMIP5 projections will resolve this issue in the future, existing reliable projections leave the problem to be resolved. The CMIP3 downscaled CSIRO Mk3 climate system model projections in this research are on a monthly timescale while EPIC requires daily climate data for accurate simulations. EPIC contains a built-in weather generator, WXGEN, which for a given set of parameters for each month simulates daily climate. WXGEN, however, uses the same parameters to generate weather across the entire period of interest, which is acceptable in many EPIC applications. Due to the climate change focus of this research using the IPCC A1B scenario over the next 30 years, the inputted generation parameters for EPIC instead need to change yearly. To accommodate this, the MODAWEC daily weather generator is used with the CSIRO Mk3 monthly data inputted to generate daily temperature and precipitation projections for Humboldt and Webster counties across the period 2011-2040.

EPIC validation

Validation of the EPIC model can be an extensive process, here an outline of the three stage validation process used in this paper is presented. First, simulated yield data for Humboldt and Webster counties is compared to actual county average yields over a historical period. The historical yield data used, from 1990-2009 (less 1993), is from USDA NASS, but 1993 is excluded from the validation process due to catastrophic flooding that year making the data unrepresentative of the production process (which was also the case in 2010). The EPIC average yields for the two decade period were 3.23% and 1.76%, respectively, off actual yields.

Next, a regression is conducted of actual yields against EPIC simulated yields for the representative farms in each county. Including a variable for time and removing two non-representative years due to significant weather events, the simulated models for both counties demonstrate an explanative factor of 78.9% in non-irrigated corn yields from 1990-2010 (less 1993 and 2010). This level of explanatory power falls well within acceptable EPIC usage in the discipline. Figures 6 and 7 are scatterplots of actual versus simulated yields for Humboldt and Webster counties.

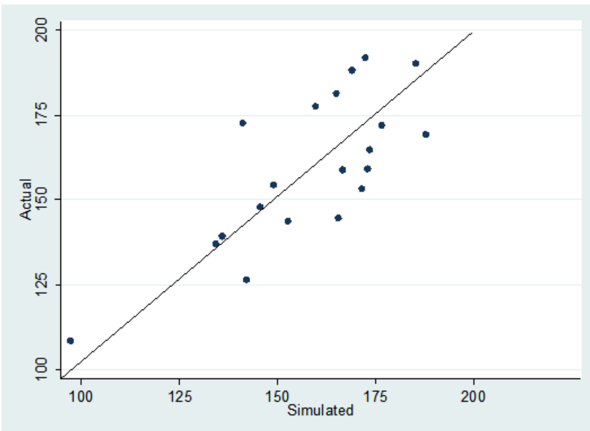

Figure 6. Scatterplot of simulated versus actual yields for Humboldt County, Iowa using EPIC.

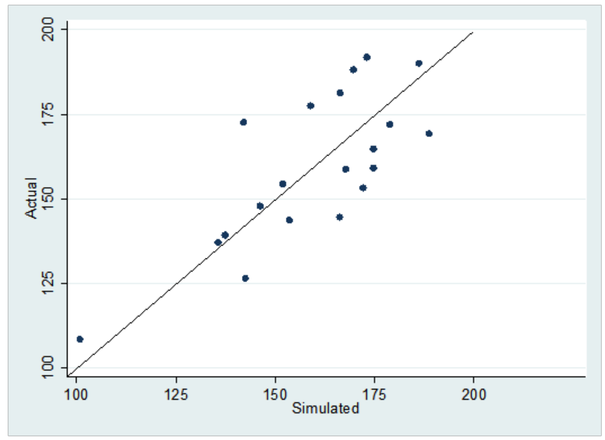

Figure 7. Scatterplot of simulated versus actual yields for Webster County, Iowa using EPIC.

Finally, the responsiveness of EPIC calibration is compared to work done by others in the field. Brown and Rosenberg (1997) present an extensive matrix of EPIC responsiveness to changes in simulated weather factors. Using farms representative of the Missouri-Iowa-Nebraska-Kansas (MINK) region, Brown and Rosenberg assess the impact of changes in single climate variables and compound changes in EPIC. Adjusting the weather factors of EPIC per the guidelines in Brown and Rosenberg demonstrates the model responds very similarly to their findings for Iowa production. This suggests that if my calibration is wrong, I will at least be in good company.

The EPIC model in this analysis is extensively validated. It accurately replicates yields on average over the past two decades, explains a large proportion of the variability seen in the period, and responds within expectations set by research published in the field.

Simulation results

In all simulations the quantity of fertilizer is held constant while the timing of its application is varied across model runs. Best management practices are determined within the defined production environment. Fertilizer quantities are at levels comparable to production practices, which even in optimized application cannot completely eliminate nitrogen stress in every year. Note, while fertilizer quantity is set, a technological improvement trend is included in the model (through the parm editor), which linearly approximates improvements in agricultural technology, including effectiveness of fertilizer over time. This simulation is intended to replicate real world production and so an extensive production pre-run is used in the validation process and production runs. A pre-run of several years is consistent with real world conditions, especially in Iowa. Rather than the first year of production occurring in virgin soil, it is part of continuous production. Agriculture is a staple of Iowa's economy, and it would be unreasonable to simulate production otherwise, and so an extensive production pre-run is utilized.

Figures 8 and 9 present the results of delayed fertilizer inputs in Humboldt and Webster counties on yields for the historical period 1990-2010 and projected 2011-2040 A1B based climate scenario. As previously discussed, it is reportedly a commonly held belief that a delay in fertilizer, specifically nitrogen, causes irreparable yield loss in corn production. However, in this simulation corn-soybean production, yields significantly increase with an application delay. Yield maximization is identified when fertilizer is applied at four to six weeks after planting. A 3.27% (5.18 bushels/acre) yield increase was possible in the 1990-2010 period while a 2.38% (4.22 bushels/acre) increase remains possible on average in 2011-2040 under the climate change scenario. A yield increase from delaying fertilizer application is consistent with some agronomical research on corn production and in contrast to others. Scharf, Wiebold, and Lory (2002) provide an overview of such literature.

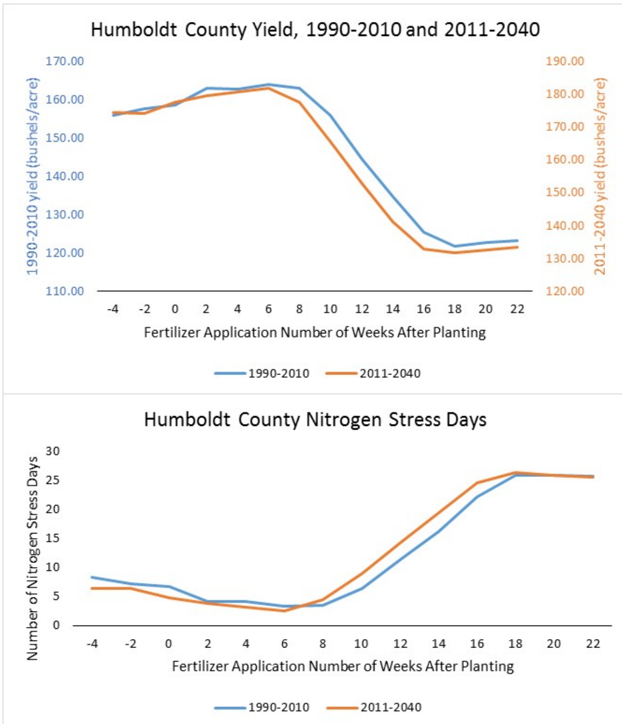

Figure 8. Fertilizer input timing yield curves and related nitrogen stress curves for Humboldt County. The blue line and scale represent the period 1960-2010 while the red applies to 2011-2040 projected production.

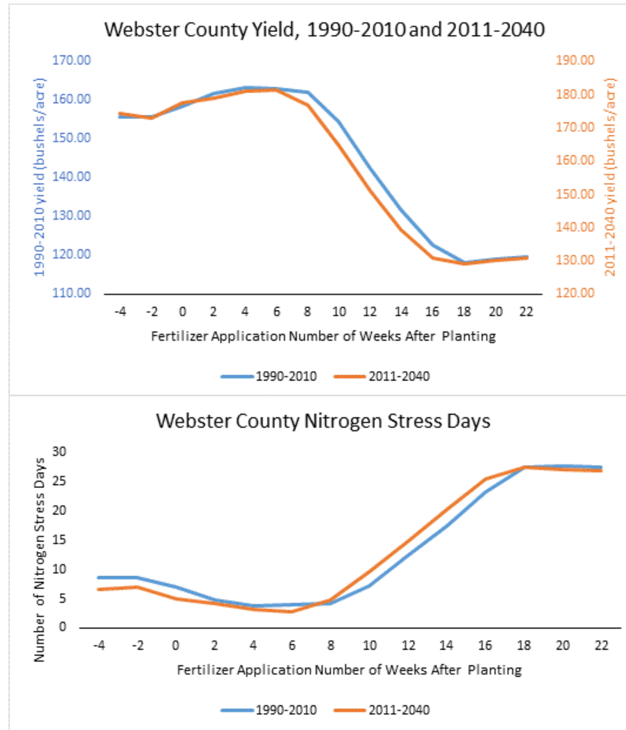

Figure 9. Fertilizer input timing yield curves and related nitrogen stress curves for Webster County. The blue line and scale represent the period 1960-2010 while the red applies to 2011-2040 projected production.

The use of a corn-soy rotation versus corn following corn production is thought to be a significant factor in the yield increases from delaying inputs seen in the results. The nitrogen supplementing characteristic of soybeans is likely providing enough nitrogen during early growth stages of corn, but is insufficient to sustain optimal growth beyond the approximately six week point into seasons on average. Fertilizer applications at the six week point provide sufficient nitrogen to sustain fertilizer stress free-growth through the balance of the season. Fertilizer applications earlier than six weeks allows nitrogen stress later in the season while fertilization later in the season leads to nitrogen stress earlier in the season as soy crop provided nitrogen is used up. Note the difference in results between Humboldt and Webster counties, the differences in soil composition cause the rate of nitrogen loss and availability to differ in the otherwise same production environments.

In figures 8 and 9 the shape of the input timing dependent yield curves change between 1990-2010 and 2011-2040. This is a result of changes in annual CO2 concentrations, monthly precipitation, and minimum/maximum temperatures as all other production parameters, less the timing of fertilizer application, are constant. In both figures, yield scales for 1990-2010 are on the left axis while scales for 2011-2040 are placed on the right axis. Production results for the 1990-2010 and 2011-2040 have been overlaid, allowing clearer assessment of changes in the curves despite generally higher yields in 2011-2040 due to technological improvements. In both locations, yield drops off earlier in the yield curves in 2011-2040. Changes in how rapidly degree-heat unit requirements are met and thus nitrogen is consumed by the crop is a likely primary reason for changes in the input timing dependent yield curves. These results suggest fertilizer should be delayed in corn production components of corn-soybean rotations, even without the use of a risk reducing decision making process. However, the input delay rationale in section four could lead to an input point even later than the yield optimizing input point depending on the timing of loss events within seasons.

Clearly other factors are influencing farmer decisions on corn input timing. Perhaps implicit knowledge on yield variability with input timing is the culprit providing disincentives for adoption of delayed input habits. Figure

10 displays how standard deviation in yield is projected to change under delayed input strategies. In the recent production period it is clear yield variability would have changed little with fertilizer input delays as late as six weeks after planting. While changes in yield variability haven't traditionally been a factor then, this issue is expected to play a greater role in coming decades. Projections under the simulation's climate change model are expected to increase yield variability significantly with a shift in fertilizer application from planting to six weeks into the season. A producer who is risk averse and yet doesn't expected total losses such that input delaying would reduce costs would be further discouraged from changing practices in the future.

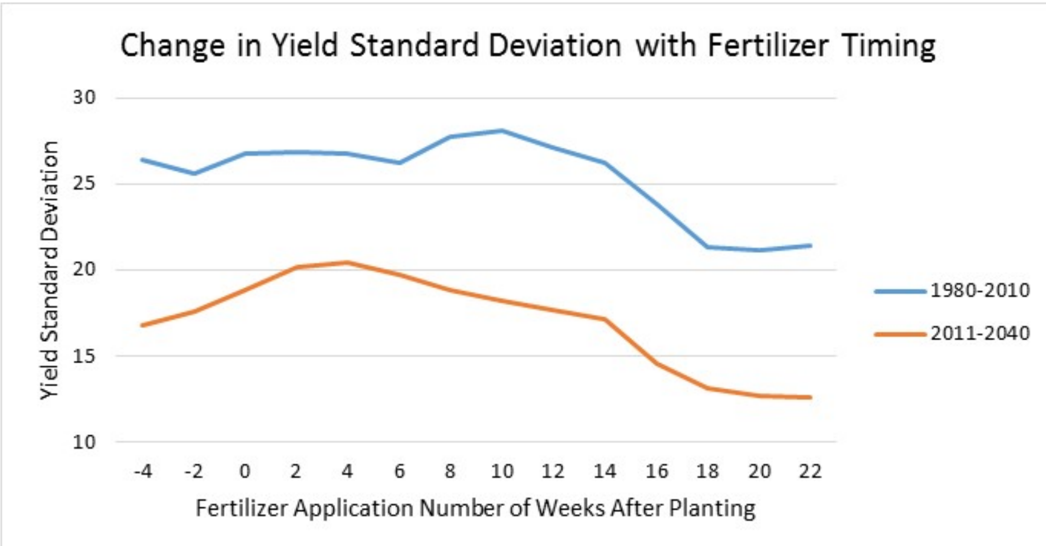

Figure 10. Standard deviation of yields in Humboldt county under different fertilizer input timing strategies. Blue line represents simulated runs for period 1980-2010 under historical weather conditions. Orange line represents simulated runs for 2011-2040 under aforementioned climate change scenario. This outcome is not significantly different for Webster County.

Limitations

The results of this EPIC simulation, unlike the decision making model, are highly condition specific. To find the optimum input timing for any site, a tailored EPIC simulation or similar agronomical analysis should be performed. And having relied on a climate model for the period 2011-2040, the accuracy of this simulation is also dependent on closeness of the climate model to actual climate change experienced in the area.

Discussion

The evidence suggests both incentives and disincentives exist to delay agricultural inputs. EPIC simulations of Humboldt and Webster counties indicate mean yield gains are possible under both current and projected climate conditions. A counterfactual using corn price data from Iowa State University puts the value of this incentive at $14.56 per acre per year on average in the period 1990-2010 (Iowa State University, 2014). Another incentive exists as a method to mitigate risk. For the geographical area of interest, while FEMA disaster declarations occurred throughout the period of interest, only one flood incident was of such scale to consider crops a total loss on a county scale. The 1993 disaster also occurred at a point within the season such that a six week input delay strategy, as suggested by EPIC's simulated yield data, would have also been effective in reducing losses. Using the same Iowa State University price data, the value of this incentive was approximately $103.51 per acre in 1993 and on average $127.86 from 1990-2010 in any year in which a total loss is incurred (price of fertilizers, application, and cost of harvest per the decision making model in this paper). On large scale farms these potential profit increases and cost decreases are potentially very large. However, EPIC simulated yields also suggest a change in variation of yields with delayed input strategies. Changing from an at-planting to six week delayed input strategy was shown to only slightly increase yield variance in the historical period but will significantly increase it over coming decades. Clearly then, a corn-soy producer, if knowledgeable about these incentives must balance yield increases and cost savings during disasters against consistency of yields in making an input timing decision. Policy options to exploit these incentives also clearly exist due to crop insurance, futures, and other sorts of purchase agreements.

Natural incentives do exist, with potentially substantially remunerative outcomes, yet such outcomes will be dependent on specific field conditions. Therefore policy should focus on information gathering and sharing and encouraging farmers to experiment with fertilizer delaying. Because total financial losses will be lower in years where disaster strikes before fertilizer application, such savings warrant lower payouts and costs to multi-peril crop insurance (MPCI). Modification of USDA RMA policy, through which MPCI rates are set, could allow discounts for farmers who demonstrate use of a delayed fertilizer strategy. Alternately, the government subsidizing farmer premiums, contingent on delayed application of fertilizer, say over a few growing seasons, could be a relevantly similar yet politically easier to implement alternative. However, contingent subsidies are temporary in nature while insurance discounts are a more permanent option. Due to the strength of incentives in this imperfect information environment, an information campaign could have substantial impact. Providing a packaged, simplified agronomical simulator to allow today's tech savvy producers to run similar experiments could be an efficient way to encourage change. A series of field experiments, over multiple years and input strategies to confirm these results, would also be helpful. Pairing these two information methods, field experiment publication with a simplified crop simulator calibrated to allow farmers to easily compare their field conditions to the experiment's, would likely further enhance each tool's effectiveness. While presented here to encourage discussion, these policy options will be explored in greater detail and placed in historical context where possible in subsequent research.

Conclusion

Delaying agricultural inputs in an environment of uncertainty may reduce exposure to risk for non-irrigated agricultural producers. Agricultural input delays can be assessed for a given location using the EPIC model. Conditions modeled for Humboldt and Webster counties suggest non-irrigated corn yields can be enhanced by delaying fertilizer application until 4-6 weeks after planting. This result held in simulations of historical as well as projected conditions through 2040. However, under future conditions there may be an increased risk of loss if fertilizer is delayed too long. Input decision making to reduce risk, when compared to declared disaster frequency, also suggests an input delay strategy, of perhaps even greater than six weeks depending on producer preference and exposure to risk within the county. And while yield variability hasn't played a role in fertilizer timing practices up to a six week delay historically, it will play a greater role as a disincentive in future production. Even still, current and recent input prices to corn production should make such an input delaying strategy enticing to all but the most change and yield variability averse producers. Policies to entice producers to try out such alternative practices may only be needed in the short run, to incentivize perseverance in overcoming any learning curve in increasing output and reducing production costs as well as farmer exposure to disaster related risk.

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Appendix A

Additional underlying assumptions of the model

I want to make explicit many of the additional assumptions in the model:

1. Price and quantity at market reflect the value received by farmers.
2. Producers are rational profit maximizers within the confine of a specific crop.
3. If expected profit (π_e) is positive, producers will produce during the appropriate season.
4. Information about π_e in a season improves, as uncertainty decreases with progression of the season. For each day that passes in a season, knowledge of how similar the current crop is to what the final product will look like improves on average.
5. Farmers have two significant input points (Magnan, Lybbert, Mrabet, & Fadlaoui, 2011): I_1 at planting and I_2 at a later growth stage, plus I_H which is harvest.
6. Input costs are fixed across a season (labor, fertilizer, defensive expenditures, etc), later it may be considered costs can change within a season due to adoption of input delaying practices.
7. Farmers can change or modify machinery in the long run to accommodate new farming strategies.
8. Related to number 7, machinery good at later stages in a season is assumed to also be efficient at planting.
9. Constant returns to scale is assumed in this model. In practice this is approximately the case as only farmers of a size capable of profit with the input prices available will be in business. Related, smaller farms can input share or rent at a small difference from larger farming operations.
10. Homogenous production across a farmer's acreage (field homogenization).
11. Rain fed farming operations face greater uncertainty due to weather than irrigated producers.

Appendix B

Input decision making model in no-till agriculture

Under no-till (*NT*) agriculture, the benefit of delaying inputs is slightly greater when an area is hit by catastrophic weather events. For the traditional farmer, equations (2.2), (2.3), and (2.4) describe their input schedule, harvest decision, and full input decision at planting. But for *NT* farmers these equations become:

$$\pi_e = P_e Q_e - I_1(L - L_L, S, F, D) - I_H(H + L_L) \quad (2.2_{NT})$$

$$P_e Q_e < I_H + L_L \quad (2.3_{NT})$$

$$\pi_e = P_e Q_e - C(L, S, F, D, H) \quad (2.4_{NT})=(2.4)$$

Here it is assumed *NT* practices do not antiquate input L_L, and instead reallocate it from early season field preparation to an equal amount of post-season field maintenance. Note equation (2.4)=(2.4_{NT}) as the reallocation of labor is within each season.

The delayed input farmer experiences the following changes to equations (2.5) and (2.6) under *NT*:

$$\pi_e = P_e Q_e - I_1(L - L_L, S, D) - I_2(F) - I_H(H + L_L) \quad (2.5_{NT})$$

$$\pi_e = P_e Q_e - I_1(L - L_L, S, D) - I_2(F, H, L_L) \quad (2.6_{NT})$$

And so under *NT* production, equations (2.10) through (2.13) become

mild event, one-decision farmers lose $\quad -\pi = C(L, S, F, D, H) - PQ \quad (2.10_{NT})=(2.10)$

or catastrophic event lose $\quad -\pi = C(L - L_L, S, F, D) \quad (2.11_{NT})$

and

mild event, two-decision farmers lose $\quad -\pi = C(L, S, F, D, H) - PQ \quad (2.12_{NT})=(2.12)$

or catastrophic event lose $\quad -\pi = C(L - L_L, S, D) \quad (2.13_{NT})$

From comparing equations (2.10) through (2.13) to equations (2.10_{NT}) through (2.13_{NT}), NT only makes a difference in profit if catastrophic events occur if traditional tillage and no-till agriculture produce the same yields. Magnan, Lybbert, Mrabet, and Fadlaoui's (2011) discussion of no-till agriculture in Morocco as a means to mitigate drought then are only applicable to developing economies with low levels of agricultural mechanization.